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Iterative non-deterministic algorithms in on-shore wind farm design: A brief survey

Salman A. Khan [a,*], Shafiqur Rehman [b]

[a] Department of Computer Engineering, University of Bahrain, Sakhir, Kingdom of Bahrain
[b] Research Institute, King Fahd University of Petroleum & Minerals, Dhahran-31261, Saudi Arabia

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ABSTRACT

Wind farm layout design is a complex optimization problem consisting of number of design objectives and constraints. Different variations of this problem have been solved using several optimization techniques. Iterative heuristics are well-known optimization techniques that have been applied to a variety of complex optimization problems. This paper briefly outlines the design issues and constraints involved in the wind farm layout design, computational complexity of the problem, and single-objective and multi-objective aspects of the problem. The main focus of the paper is a brief survey of all iterative non-deterministic algorithms that have been applied to solve the wind farm layout design problem.

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* Corresponding author.
E-mail addresses: engr.ahmeds@gmail.com, sakhan@uob.edu.bh (S.A. Khan), srehman@kfupm.edu.sa (S. Rehman).

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1. Introduction

Wind power has evolved as one of the fastest growing sustainable energy resources, as the conventional sources of fuel, which constitute fossil and other carbon fuels, are rapidly diminishing. The idea of utilizing wind power at a massive scale has received considerable attention in the past few years, which has resulted in identifying four major areas of investigation [1,2]. The first area deals with the sensors and instrumentation used for wind measurements. The second area is concerned with the evaluation of potential of wind energy for a given region by employing various statistical approaches. The third area is focussed on the design and characterization of wind turbines. The fourth area is concerned with the design and development of wind farms, which requires efficient (rather optimal) placement of wind turbines in a wind farm, while considering various design objectives and constraints.

According to the recent statistics by Global Wind Energy Council, global wind power installations increased by 35.8 GW in 2010 [3]. This brings the total installed wind power capacity up to 194.4 GW, a 22.5% increase on the 158.7 GW installed at the end of 2009. The new capacity added in 2010 represents investments worth EUR 47.3 billion (US Dollars 65 bn). For the first time in 2010, more than half of all new wind power was added outside of the traditional markets in Europe and North America. This was mainly driven by the continuing boom in China, which accounted for nearly half the new wind installations (16.5 GW). Furthermore, other developing countries also expanded their wind capacity, including India, which added 2.1 GW in 2010, Brazil (326 MW), Mexico (316 MW), and 213 MW were installed in North Africa (Egypt, Morocco, and Tunisia). Serious attention is also being given to wind energy in Lebanon [4], Algeria [5,6], Cameroon [7], Serbia [8,9], and Oman [10].

A number of commercial software programs are available in the wind energy industry to facilitate the wind farm design process. Despite the intelligence and sophistication of these programs, human intervention may still be required during the design process, to come up with better layout designs than generated by the software itself. Therefore, researchers have employed various computational intelligence techniques for wind farm layout design problem. Such techniques have proven to be highly efficient for solving complex optimization problems in many disciplines of engineering and science. Being classified as a complex optimization problem, the wind farm layout design problem has attracted researchers to solve different versions of this problem using various computational intelligence techniques [11].

Due to the complexity of the wind farm layout design problem, exact optimization approaches such as linear programming, branch-and-bound, dynamic programming, and backtracking [12], etc., cannot be utilized. The reason is that these algorithms cannot efficiently deal with the NP-hard nature of the problem. In contrast, approximation algorithms, commonly known as *heuristics*, are the most suitable choice to solve the said problem. Approximation algorithms generally solve an optimization problem in a reasonable amount of time, since they search the solution space intelligently, and focus on those sub-spaces of the total solution space which have a higher probability of finding a high quality, feasible solution. In many cases, approximation algorithms are even able to find near-optimal or optimal solutions. In contrast, exact algorithms are able to find a high quality solution (and even an optimal solution), but at the expense of immense computational time, mainly because exact algorithms assess each and every solution in the solution space.

Approximation algorithms are further categorized into two groups: *constructive* and *iterative*. Constructive algorithms produce a complete solution by making deterministic moves. Constructive techniques are faster than iterative approaches, but in most cases produce solutions of unacceptable quality. For highly constrained problems, constructive techniques may even fail to find a feasible solution. Moreover, due to deterministic moves, constructive algorithms always produce the same solution at the end.

Iterative algorithms attempt to improve a complete solution by doing a controlled walk through the state space [13]. Generally, iterative schemes are categorized into two sub-categories: schemes which only accept good moves, i.e., perturbations leading to better quality solutions like local search, and schemes which can accept bad moves like Simulated Annealing (SA) [14,15], Genetic Algorithms (GA) [16,17], Differential Evolution (DE) [18], Tabu Search (TS) [19], Simulated Evolution (SimE) [20,21], Stochastic Evolution (StocE) [22,23], and Swarm Intelligence (such as Ant Colony Optimization (ACO) [24], Particle Swarm Optimization (PSO) [25], and Honeybee Colony Optimization [26]). Such search schemes are said to possess a hill-climbing property, enabling them to escape local optima and hence discovering better quality solutions. It is worth mentioning that these schemes perform non-deterministic moves, and therefore do not reach exactly the same solution at the end (as opposed to constructive algorithms).

During the past two decades, considerable attention has been given to the use of iterative non-deterministic algorithms in the field of wind energy. However, the literature lacks adequate

survey and review papers on this aspect. The most comprehensive survey covering the use of optimization techniques in the domain of renewable energy is by Baños et al. [27]. However, even the focus of the survey by Baños et al. is very broad in the sense that it covers all optimization algorithms in all sub-fields of renewable energy. To date, no review has been reported in the literature which specifically looks at the research done on one key problem in the domain of wind energy, which is the optimal layout design of on-shore wind farms, and using iterative non-deterministic optimization techniques applied to this specific problem. This gives the motivation to carry out the survey reported in this paper. Therefore, the objective of this paper is to give a flavor of various iterative non-deterministic techniques to researchers in wind farm layout design as well as to provide a brief compilation of status of the application of the above techniques to the problem. We believe this to be the most comprehensive survey of the reported applications of iterative non-deterministic algorithms to the wind farm layout design problem. These algorithms include Genetic Algorithms (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). The first three algorithms differ from the last one in the sense that they are population-based algorithms. That is, in each iteration, they maintain a population of solutions and perform certain operations on this population to generate new solutions. In contrast, SA maintains a single solution throughout its execution and perturbs this solution to evolve to a better solution. The above techniques have been successfully applied to a number of optimization problems in the disciplines of science, medicine, engineering, and business.

The rest of the paper is organized as follows. Section 2 briefly describes the wind turbine placement problem with associated objectives and constraints. Section 3 briefly describes the genetic algorithm followed by its all reported applications to wind farm layout design problem. In Section 4, differential evolution is briefly introduced with its application to the concerned problem. Section 5 gives a short introduction of PSO along with its applications to the problem. A short discussion on SA and its application to the problem under study is presented in Section 6. A brief comparison of algorithms with respect to the wind farm layout design problem is presented in Section 7. A projection of further research opportunities and challenges is presented in Section 8. Finally, concluding remarks are given in Section 9.

2. Overview of the wind farm layout design problem

The wind farm layout design problem requires optimal placement of wind turbines in a wind farm. This optimal placement is necessary in order to minimize the power loss due to different effects such as *wake decay*, *transmission line loss*, and *turbulence*, etc. Moreover, an optimal placement of wind turbines also has a significant effect on the costs associated with installation, functioning, and maintenance of these turbines. In broader terms, the wind farm layout design problem can be defined as follows:

"Given a wind farm location and a number of wind turbines, the turbines need to be placed in the wind farm such that the design objective(s) are optimized, while satisfying the design constraint(s)."

In view of the above definition, a number of design objectives and constraints can be defined, as proposed in the literature. With regard to the design objectives, the fundamental aims of a wind farm are to minimize capital and operating costs and to maximize energy production [28]. These two objectives in turn relate to maximizing profit from the farm, which is considered another important objective. Environmental aspect has also been considered as another important factor with minimizing the level of noise generated by the wind farm as another objective [29].

There are many factors involved that make up the total cost of the wind farm. According to several studies, the principal factor is the cost of turbines, which depends on turbine rated capacity, type, and hub height. This factor constitutes 65–75% of the total cost of the wind farm [30]. The second major cost factor is the electrical infrastructure, contributing 10–15% [30]. The cost of civil works also has an impact, comprising of 5–10% of the total cost. The remaining 10% consists of installation and other miscellaneous costs [30]. In addition to these cost factors, operating costs also play an important role. Energy production also depends on a number of factors such as losses due to the wake effect, electrical, and unavailability. It is extremely important that wind farms be designed in such a way so as to minimize these losses as much as possible.

There are also several constraints that should be considered during the wind farm layout design. These include environmental constraints, technical and design constraints, and setback constraints. Environmental constraints are concerned with the wind farm terrain and climate of the area. Technical constraints deal with the technical specifications of the wind turbines, compatibility of parts with each other, and the electrical system with which it is to be integrated. Moreover, design constraints dictate a certain minimum distance between the turbines, to minimize wake, turbulence, and other associated effects. Setback constraints impose restrictions on the turbine locations. For example, it would be impossible to install turbines too close to houses, military facilities, airports, or boundaries of a non-cooperative landowner [31]. Furthermore, turbines cannot be installed in locations that may visually impact the landscape, or along the migration path of birds, etc. [31].

Note that the objectives and constraints mentioned above represent a general set, and a subset of these objectives and constraints may be applicable to certain situation depending on the requirements as well as topographic and demographic structure of the site chosen for the wind farm.

2.1. Computational complexity of the wind farm layout design problem

The placement area, where turbines are placed, can be addressed by either a discrete or a continuous representation. In either case, the solution space is huge. Consider a layout design problem with an area of $40D \times 40D$, where D represents the wind turbine rotor diameter. If discrete representation is used and the area is divided into 100 equal size squares, then each square will have an area of $16D^2$. This will result in the turbine placement problem with a size of 2^{100}, considering whether a square contains a turbine or not. Thus, the wind farm layout design problem can clearly be classified as an NP-hard problem. In this situation, exact algorithms would fail due to their high computation time. It would be therefore essential to employ some heuristic to intelligently search the solution space and reach an optimal or near-optimal solution in a reasonable amount of time.

2.2. Single-objective and multi-objective approaches to the wind farm layout problem

As mentioned above, several design objectives exist that could be optimized during the wind farm layout design process. Depending on the approach adopted by the designer, single- or multiple-objectives can be considered. This in turn results in the problem being Single-Objective Optimization (SOO) or Multi-Objective Optimization (MOO). In SOO, a single-objective is optimized during the optimization process. The definition of

SOO can be further extended to many objectives which are *non-conflicting*. That is, if there are a number of objectives which all require maximization, and maximizing one objective automatically maximizes others, then it will also be a case of SOO. Generally, when a wind farm is to be developed, the focus is on either to optimize cost, or optimize energy output. In the former case, the main constraint is the budget of the whole project which is known *a priori*. In this scenario, the number of wind turbines needs to be found in advance to satisfy the budget limitation, and the issue is mainly concerned with optimally placing these turbines in the wind farm. In the latter case, the required energy output is known, and the issue is to find as how many wind turbines are required, as well as to optimally place these turbines to meet the required energy output.

The complexity of optimization process increases when multiple, *conflicting* objectives need to be optimized simultaneously. In such situations, optimizing one objective results in the deterioration of other objective(s). In other words, if both cost and power output need simultaneous optimization, then the focus is on how to maximize the power output while minimizing cost. In this situation, neither the required cost nor the number of wind turbines required are known. This is where *Multi-Objective Optimization* (MOO) comes into picture. In this type of situation, a trade-off is needed to obtain a "balanced" solution; a solution (or rather a set of solutions, referred to as the *Pareto front*) that has the best possible values of all objectives. MOO techniques are able to produce the best trade-off between the two objectives. A number of review papers concerning the use of MOO approaches

Table 1
Characteristics of different wind farm layout design problems considered with GA. HH represents hub height and D represents rotor diameter.

Ref.	Year	Grid	Wind scenarios	Wind turbine height and rotor diameter	Wake decay model
[39]	1994	Square shaped with square cells	(1) Unidirectional wind with constant intensity (2) Variable wind direction and constant intensity (3) Variable wind direction and variable intensity	HH = 60 m D = 40 m	Jensen
[40]	2005	Same as [39]	Same as [39]	HH = 60 m, D = 40 m	Jensen
[41]	2007	Unspecified	(1) Fixed wind intensity, unspecified wind direction (2) Variable wind intensity, unspecified wind direction	HH = 50 m for cases 1 and 2 and variable between 50 m and 100 m for case 3 D = unspecified	Jensen
[42]	2007	Same as [39]	Same as [39]	HH = unspecified D = 40 m	Katić
[43]	2009	Amorphous, with rectangular cells	Actual conditions of the site	HH = 50 m D = 48 m	Jensen
[44]	2009	Same as [39]	Same as [39]	HH = unspecified D = 40 m	Katić
[45]	2009	Same as [39]	(1) Unidirectional wind with constant intensity (2) Variable wind direction and constant intensity	HH = 60 m D = 40 m	Katić
[46]	2009	Unspecified	Same as [39]	Unspecified	Developed own model
[47]	2009	Unspecified	Same as [39]	Unspecified	Same as [46]
[48]	2009	Straight line in flat terrain	(1) Fixed hub height and uni-directional wind flow (2) Fixed hub height and bi-directional wind flow (3) Variable hub height and bi-directional wind flow	HH = unspecified D = 77 m	Jansen
[49]	2010	Same as [39]	Same as [39]	HH = 60 m D = 40 m	Modified Jensen
[50]	2010	Unspecified	Same as [39]	Unspecified	Jensen
[58]	2010	Same as [39]	Same as [39]	HH = 60 m, D = 40 m	Frandsen
[51]	2010	Unspecified	Variable direction with variable intensity	HH = 80 m D = 77 m	Developed own model
[52]	2010	Same as [39]	(1) Three scenarios considering fixed direction and different wind speeds (2) Real wind distribution	HH = unspecified D = 47 m	Katić
[53]	2010	Same as [39]	nine different cases with different wind directions	HH = variable between 60 m and 100 m	Frandsen
[54]	2011			D = unspecified	
[55]	2011	Same as [53,54]	Same as [53,54]	Same as [53,54]	Same as [53,54]
[56]	2011	Amorphous, with square cells	15 wind speeds with no mention of direction	HH = unspecified D = 90 m	Jensen
[57]	2012	Amorphous, with square cells	Actual conditions of the site	HH = 60 D = 40 m	Jensen
[29]	2012	Square shaped	Unidirectional wind with constant intensity	HH = 60 D = 40 m	Jensen

in the domain of renewable energy have been published in the literature [32–34]. Although these papers do not directly address the issues governing MOO in wind farm layout design problem, yet they provide useful guidelines and directions.

2.3. Centralized versus distributed algorithms

Any iterative non-deterministic algorithm can be implemented either in *centralized* or *distributed* mode. In the centralized approach, all algorithmic processes are run on a single computer. The main advantage of the centralized approach is that it is easy to implement. However, since iterative non-deterministic algorithms are computationally expensive, generation of final results takes a significant amount of time. Furthermore, centralized algorithms are susceptible to single point of failure (for example, the computer may crash) which results in complete halt to the execution of the algorithm.

In contrast to the centralized approach, distributed mode is implemented on several computers interconnected with each other, generally through a localized network. Computers interact with each other to perform a computation task. In the distributed approach, the computational process is divided into many tasks, and all computers perform their assigned tasks in parallel. At the end, all computers send their results to the main computer whose job is to coordinate the computational activities among computers. The main advantage of the distributed approach is that since tasks are distributed and are performed in parallel, it takes considerably less time to obtain the final results as compared to the centralized approach. Another advantage is that the arrangement is fault tolerant, since failure of one or two computers does not significantly affect the overall functioning of the algorithm. However, major disadvantages of the distributed approach are in terms of huge hardware requirements (computers, networking infrastructure, etc.) as well as complexity in implementation.

3. Genetic algorithms and wind farm layout design problem

Genetic Algorithm (GA) is a popular and an effective optimization algorithm, which emulates the natural process of evolution as a means of progressing toward an optimum. Initially suggested by Fraser [35], Fraser and Burnell [36], and Crosby [37], and popularized by Holland [16], the GA was inspired by Darwinian theory [38]. The foundation of GA is based on the theory of natural selection, whereby individuals having certain positive characteristics have a better chance to survive and reproduce, and hence transfer their characteristics to their offspring. GA operates on a *population* (i.e., a set of solutions), whereby each member of the population is referred to as *chromosome*, which represents an individual solution. A chromosome is comprised of individual elements, called *genes*. During each iteration, a new set of chromosomes, called *offsprings* is generated. Each offspring is a result of four genetic operators, namely *selection*, *crossover*, *mutation*, and *inversion* (optional). These operators are repeatedly applied to a collection of solutions to generate the new offspring. The algorithm returns a final solution once a pre-defined stopping condition is met. The important algorithm parameters are the population size, crossover rate, and mutation rate, whose values have a significant impact on the quality of the final solution. Therefore, these parameters need proper tuning for best results.

Among all optimization methods reported in the literature, GA has been the most utilized algorithm to solve the wind farm layout design problem. Below, a chronological brief survey of GA's application to the said problem is provided. Table 1 provides certain important characteristics of the problem considered, while Table 2 enlists the GA related main characteristics in the surveyed papers.

3.1. Multi-objective GA of Mosetti et al.

The work by Mosetti et al. [39] in 1994 was the first attempt to apply GA to the wind farm design problem, with the objective of optimally placing the wind turbines in the wind farm. The strategy behind this is that if each turbine in the region of interest (i.e., the wind farm) is placed in its optimal position, then the cost of the wind farm can be reduced, while the energy output can be maximized. The problem was formulated as a multi-objective optimization problem, with the cost per year of the wind farm and total energy produced per year, as the two optimization objectives. Each of these objectives was aggregated in a single equation, and weights were assigned to each individual objective. The value of these weights decided the level of preference given to each optimization factor. The optimization function is mathematically represented as

$$Objective = w_1 \frac{1}{P_{tot}} + w_2 \frac{Cost_{tot}}{P_{tot}} \tag{1}$$

Table 2
Characteristics of the GAs considered in the review.

Ref.	GA type	Optimization approach	Solution representation
[39]	Centralized	Multi-objective	Binary string
[40]	Centralized	Single-objective	Binary string
[41]	Centralized	Single-objective	Integer string of variable size
[42]	Distributed	Single-objective	Binary string
[43]	Centralized MOGA	Multi-objective	Binary string
[44]	Hybrid distributed	Single-objective	Binary string
[45]	Centralized	Single-objective	Binary string
[46]	Centralized	Single-objective	Unspecified
[47]	Centralized	Single-objective	Unspecified
[48]	Centralized	Single-objective	Binary digits
[49]	Centralized	Multi-objective	Binary string
[50]	Centralized	Single-objective	Binary string
[58]	Centralized	Single-objective	Integer string of variable size
[51]	Centralized	Multi-objective	Unspecified
[52]	Centralized	Single-objective	Binary string
[53,54]	Centralized	Single-objective	Integer string of variable size
[55]	2-level nested	Single-objective	Integer string of variable size
[56]	Centralized	Single-objective	Integer matrix of variable size
[57]	Centralized	Multi-objective	Binary string
[29]	Centralized	Multi-objective	Integer string

where P_{tot} is the total energy produced in one year, w_1 and w_2 are arbitrarily chosen weights, and $Cost_{tot}$ is the cost/year of the whole wind farm. For wake decay effect, a Jensen model based approach was employed. The solution was represented as a binary string of chromosomes, where each chromosome represents a certain configuration of turbines in the wind farm. A square shaped terrain was considered, which was divided into 100 equal sized square cells, where each cell represented a possible turbine location. The turbine is located at the center of the cell, and the side size of this cell was equal to five turbine diameter, or 5D. This resulted in the total size of the wind farm equal to $50\text{D} \times 50\text{D}$. Three different scenarios with regard to wind intensity and wind direction were considered. Comparison of GA produced configuration with a random configuration showed GA's superior performance, but at the expense of higher runtime.

3.2. Single-objective GA of Grady et al.

Grady et al. [40] was the second reported attempt of employing GA for wind farm design. The work came in 2005, almost 11 yrs after the work of Mosetti et al. The basic approach of Grady et al. was more or less similar to that of Mosetti et al. For example, the same scenarios with regard to wind intensity and wind direction were considered. A Jensen model based approach was used for the wake decay effect. The problem was formulated as a discrete optimization problem, with solutions being represented as binary strings of chromosomes. A square grid of 100 square cells was assumed, with the width of each cell equal to 5D, resulting in wind farm size of $50\text{D} \times 50\text{D}$. The main difference from Mosetti et al.'s work was the objective function. A single objective was optimized, which was the minimization of cost per unit of energy produced, as given by the following equation:

$$Minimize\ \frac{Cost}{P_{tot}} \tag{2}$$

where P_{tot} is the total power extracted by all of the N turbines in the wind farm, and $Cost$ is calculated using the following equation:

$$Cost = N\left(\frac{2}{3} + \frac{1}{3}e^{-0.00174N^2}\right) \tag{3}$$

In addition to optimal configurations, results included fitness of the solutions, total power output, efficiency of power output, and number of turbines for each configuration. The algorithm resulted in mixed performance in comparison to results by Mosetti et al. For the first case (unidirectional wind with constant wind speed), Grady et al. reflected better performance. This was, however, not the case with the other two test scenarios.

3.3. Single-objective GA of Mora et al.

Mora et al. [41] proposed a GA to design a wind farm. One novel aspect of work of Mora et al. was that the proposed GA used variable size chromosomes, as opposed to fixed size chromosome in many previous attempts by other researchers. The reason for having a variable size chromosome was due to the fact that the approach used different number of wind turbines for each solution. To accommodate this situation, integer codification was used in the algorithm implementation. This resulted in the complicated structure of the proposed algorithm, since it was difficult to cross solutions of variable sizes.

A single-objective optimization was considered, with the objective being the maximization of the economic function Net Present Value (NPV) for a maximum number of prearranged wind generators or for a maximum value of initial investment, represented by the following equation:

$$NPV(x,i,t) = \frac{N_1(x)}{1+i} + \cdots + \frac{N_t(x)}{(1+i)^t} - IC(x) \tag{4}$$

where IC is the initial capital investment, including the cost of the wind generator, the installation, and the tower, N_k is the net cash flow of the kth year, i is the discount rate (capital cost), x is the state vector with the location and height of wind turbines, and t is the number of years spanned by the investment.

Three test cases were considered with a gird of 20×20. The first two cases considered fixed wind speed over the ground, while the third one assumed variable wind speed over a hilly terrain. The experimentation showed that the proposed GA was able to profit the investment in an optimal way.

3.4. Single-objective GA of Huang

Huang [42] utilized a distributed GA to find the optimal number and locations of wind turbines in a wind farm. Distributed GA provides a powerful strategy for searching the global optimal by dividing large population into multiple small sub-populations, while employing a mechanism of occasional exchange of some individuals between the sub-populations [17]. Huang used the Katić's wake effect model [59]. A square gird of 100 cells was considered with the cell width of 5D. A turbine is located in the center of a cell. The same three scenarios as with Mossetti et al. and Grady et al. were considered with regard to the wind intensity and direction. The problem was formulated as a single objective optimization problem, where the objective was to maximize the annual profit obtained from the wind farm, as given by the following equation:

$$profit = \left[s - \left(\frac{cost_{tot}}{E_{tot}}\right)\right] \times E_{tot} \tag{5}$$

where s stands for the estimated selling price for a KWh of electrical energy in the market and E_{tot} represents the total expected energy output (kWh) of the wind farm per year.

A discrete solution representation was assumed, with each chromosome consisting of binary values. A 1 in a location reflected the presence of a turbine, while a 0 represented the absence of a wind turbine. Thus, for a 10×10 grid, a binary string (individual) with 100 bits was created. Comparison of the proposed distributed GA was done with simple GA, and results showed a superior performance by distributed GA with regard to both solution quality and execution speed.

3.5. Multi-objective GA of Şişbot et al.

Şişbot et al. [43] proposed a Multi-Objective GA (MOGA) to design a wind farm on a real site. The MOGA applied in their work used Pareto ranking [60,61] as means of comparing solutions across the objectives. In multi-objective optimization, vectors (solutions with multiple objectives) are regarded as optimal if their components cannot be improved without deterioration of any one of the other components. A discrete solution representation was employed, where each chromosome (representing a configuration) consisted of 1's and 0's. Şişbot et al. considered Jensen's model for wake decay effect. The site selected was at the island of Gökçeada, located at the north-east of Aegean sea. Since the aim was to design a wind farm considering the conditions of this actual terrain, an amorphous grid was considered, with 100 rectangular cells, some of which were omitted to adapt the geometry of existing land geography. The minimum spacing distances were 8D and 2D for prevailing wind and crosswind, respectively. Moreover, actual wind conditions of the site were considered during the optimization process. Two objectives were

considered for the optimization. The first objective was the cost of the configuration, given as

$$TotalCost = C_{cp} + C_{op} \tag{6}$$

where C_{cp} and C_{op} are the installation cost and the operational cost, respectively. The algorithm was designed to eliminate those solutions which had higher costs than the budget ceiling of US$ 20M.

The second objective function was to maximize the power extracted from the farm, given as

$$P_{Total} = \sum_i P_{w_i} \tag{7}$$

where P_{w_i} is the power generated by turbine *i*. The results of the work revealed that MOGA with Pareto optimality could predict optimal turbine placement.

3.6. Single-objective hybrid GA of Huang

Huang [44] modified his distributed GA which he proposed in [42]. The modification came as the hybridization of distributed GA with hill-climbing approach. Hill-climbing is an iterative approach that always tries to improve the current state [44]. The improvement in hill-climbing approach is due to the fact that the approach restricts the search around the best solution found so far by exploring its direct neighborhood. This in turn reduces the execution time in reaching the best (or rather optimal) solution compared to the distributed GA. Thus, in hybrid distributed GA, global search and local search are carried out simultaneously, which allows local minimum to be avoided, and the diversity of individuals in the search process can be kept to realize an effective search [44]. Empirical results suggested that the performance of the proposed hybrid distributed GA algorithm was much better than that of the simple GA and distributed GA in both solution quality and execution speed. The proposed hybrid distributed GA reduced the execution time in the range of 88–92% as compared to that of the simple GA. Other algorithm parameters, problem formulation, solution representation, wake effect model, objective function, and test scenarios were the same as used in [42].

3.7. Single-objective GA of Wan et al.

Wan et al. [45] employed the GA to place the wind turbines in the wind farm. The novelty of their work was in the improved wind and turbines models, which were formulated into an optimal control framework to solve the wind farm design problem as efficiently as possible. The basis of their work was their claim that the models of wind distribution and of power evaluation adopted by Mosetti et al. [39] and Grady et al. [40] were relatively simple. Wan et al. employed Weibull probability distribution functions to describe wind speed annual variations. The power curves of turbines were used to evaluate the turbine power generation. As a result, the power of wind turbines, wake effects, and the total power production in the wind farm could be more accurately evaluated [45]. Wan et al. used the Katić's wake effect model. Optimization of a single objective was sought, which was to minimize the cost per unit energy, as given by Eq. (2) above. A flat and squared terrain divided into 10×10 squared cells was considered. The width of each cell was taken as 5D. Center of the cell was taken as possible position for a turbine. The solution was represented as a binary-coded string of size 100, where each location in the string could either take a 1 (representing presence of a turbine) or a 0 (reflecting the absence of a turbine). Two scenarios were considered for the study. The first scenario considered wind in only one direction with a constant average speed. The second scenario considered wind evenly distributed among 36 directions with a constant average speed. Empirical results were compared with Grady et al.'s work [40], which indicated that the proposed GA resulted in the improved wind farm performance.

3.8. Single-objective GA of Wang et al.

Wang et al. [46] proposed a new non-linear wake model, as opposed to some previous studies which used the linear wake model. The new non-linear wake model was introduced into the calculation of flat or slightly undulating topography and offshore wind farms. They combined the above model with the cost-benefit model of wind farm projects considering multiple factors as well as the benefit evaluation model of increasing the number of wind turbines in the wind farm. In addition to the above, a more complete and effective mathematical model was developed to decide the optimal configuration of wind turbines. All these refinements were then incorporated into the optimization process using a GA. A single optimization factor was considered, which was to minimize the ratio of the total investment cost and the total benefit (power generation here). In other words, the objective was to maximize the output benefit of the unit investment cost, given by

$$Minimize\ \frac{C_{total}}{P_{total}} \tag{8}$$

where C_{total} was the total investment cost and P_{total} was the power generation. The total cost, C_{total}, consisted of two factors, namely the fixed investment cost C_1 associated with the wind turbine equipment and the total running, maintenance and management cost C_2 during the period of economic appraisal [46]. Although the paper provided detailed discussion on the new mathematical models proposed, no information on the solution representation, structure, and the parameter setup of the GA was provided.

3.9. Modified single-objective GA of Wang et al.

Following their earlier work in [46], Wang et al. [47] explored the effect of different computational grids for wind farm design. More specifically, the shape of the grids, the arrangement direction of the grids, and the density of the grids were introduced to study the effect of computation grids on optimization results, while considering the actual wind and wake characteristics of wind turbines. Three different wind speed and wind direction scenarios were considered. A single objective function, as given in Eq. (8), was used. With regard to the shape of the grids, three shapes, namely square, triangle and circle were used. Results showed that square grids, generally used in optimization, are suitable for wind farms having wind conditions of a single wind direction or a single predominant wind direction. As far as distribution direction of grids are concerned, results showed that arrangement direction of computation grids had some influences on the optimal placement of wind turbines. Finally, with respect to the density of the computation grids, results showed their vitality to the optimization of wind farm configurations. Although the research paper mentioned applying GA to study the above effects, no GA specific information such as the solution representation, parameter setup, etc., was provided.

3.10. Single-objective GA of Acero et al.

Acero et al. [48] utilized GA for placement of wind turbines in a straight line (i.e., in a one-dimensional arrangement) lined-up in the direction of the wind. The optimization objective was to maximize the total power generated by a wind farm, $P(U_0)$,

mathematically represented as follows:

$$Maximize\ P(U_0) = \frac{1}{2}\rho A C_p(U_0) U_0^3 \tag{9}$$

where U_0 is the incoming free-flow wind speed, ρ is the air density, and A is the area swept by the rotor. $C_p(U_0)$ is the power coefficient of the turbine. Two constraints were considered. The first constraint was to maintain a minimal distance of 2D between two turbines. The second restriction was in terms of the geographic limits of the terrain. A virtual gene genetic algorithm (vgGA) [62] with binary digits was used. Each individual was represented by a vector of 28 bits, where the first 16 bits corresponded to the position of a turbine, the next 10 represented the height of the turbine, and the last two were the on-off bits for the first wind direction (west to east) and the second direction (east to west), respectively. A flat terrain was assumed, with the rotor diameter of 77 m. Jensen's wake effect model was used. Two test scenarios were considered. The first scenario assumed constant turbine hub height and one-directional wind flow, while the second considered constant turbine hub height and bi-directional wind regime.

3.11. Multi-objective GA of Emami and Noghreh

Emami and Noghreh [49] proposed a GA and compared their work with Mosetti et al. [39] and Grady et al. [40]. The proposed GA had some novel modifications to the previous work. One novelty was in terms of new coding approach with regard to solution representation. Emami and Noghreh utilized matrix binary chromosomes instead of numerical binary chromosomes. Matrix binary chromosomes based coding has an impact on the algorithm in reducing the time of calculation and optimizing the results. The other novelty was in terms of the objective function. It was claimed that the proposed objective function, with its adjustable coefficients, provides more control on the cost, power, and efficiency of wind farm in comparison with the objective functions of Mosetti et al. and Grady et al. Mathematically, the objective function was represented as a multi-objective optimization function, as follows:

$$g = w_1 cost_m + w_2 \frac{1}{P_{total}} \tag{10}$$

$$w_1 + w_2 = 1 \tag{11}$$

where P_{total} represents the total energy produced in 1 yr (MWatt), w_1 and w_2 are arbitrarily chosen weights, and $cost_m$ is the per unit value of cost/year of the whole wind farm. For wake decay, an approach built upon Jensen's model was employed. For wind direction and wind intensity, the same three scenarios as used by Mosetti et al. and Grady et al. were considered. A square shaped terrain was assumed, consisting of 100 equal sized square cells, where each cell represented a possible turbine location. A turbine had to be placed at the center of the cell, where the width of each cell was 5D. A discrete solution representation was assumed, with each chromosome represented as binary string of 1's and 0's. A 1 in a location indicated the presence of a turbine, while a 0 represented the absence of a wind turbine. Empirical results showed that with regard to the first scenario (unidirectional uniform wind), the new coding reduced the number of individuals (i.e., chromosomes) and required generations, while keeping its effectiveness, in comparison with the work of Grady et al. For the second scenario (uniform wind with variable direction), improved results were obtained in comparison with Grady et al.'s results, by using the new coding besides the new objective function. As for the third scenario (non-uniform wind with variable direction), the proposed approach also produced better results in terms of higher power generation and efficiency in comparison with Grady et al.

3.12. Single-objective GA of Mittal

Mittal [50] utilized GA for wind farm design to minimize the cost per unit power produced from the wind farm. The main contribution of Mittal's work was the reduction of grid spacing to 1/40 wind turbine rotor diameter (i.e., 1/40D) as compared to 5D in previous studies by Mosetti et al. and Grady et al. The same objective function, as used by Mosetti et al. and Grady et al., was employed. A discrete GA was used. Jensen's wake effect model was employed. Results were obtained for the same three scenarios adopted by Mosetti et al. and Grady et al. The obtained results revealed that the modification in grid spacing reduced cost per unit power by in the range of 11–16% for the three test scenarios.

3.13. Single-objective GA of González et al.

González et al. [58] based their approach on the work of Grady et al. The GA proposed by González et al. made use of the same test cases as by Grady et al. for the sake of comparison, but further added constraints to present a more realistic scenario. The modified test cases considered the same square shaped terrain of 2 km $\times$ 2 km subdivided into 10 $\times$ 10 squared cells, as in Grady et al. work, but with added restrictions such as the presence of a main road crossing the park from west to east, two forbidden zones, and a low load-bearing capacity zone where the foundation costs were higher. Other salient features of the GA proposed by González et al. were (1) a more realistic wind farm cost model based on the net present value of wind farm life cycle cost and (2) an improved and generalized wake decay effect based on a more accurate model proposed by Frandsen [63]. Since González et al. used a variable number of turbines for each solution, the approach of Mora et al. [41] was used with solution size of variable length, and thus using integer codification in the algorithm implementation. A single-objective optimization was considered, with the maximum economic profit of the investment in the wind farm being the objective, as used by Mora et al. [41]. Although no information on cell size was provided, the implied size was 5D, since González et al. did the testing on exactly the same scenarios as considered by Grady et al. Results showed that the proposed GA was able to reach the convergence in quite less generations, with lesser computational effort when used on test cases of Grady et al. Moreover, the proposed GA was also able to find the optimal solution for the modified test cases.

3.14. Multi-objective GA of Kusiak and Song

Kusiak and Song [51] used SPEA algorithm [64] which is based on GA, to design a wind farm for an industrial setup. They made several assumptions such as (1) the number of wind turbines were fixed and known *a priori*, (2) all wind turbines were homogeneous, i.e., all turbines had the same power output curves, and (3) wind speed at a certain location and height follows a Weibull distribution. Although they developed their own wake loss model, it was also suggested that other wake models could also be used. Optimization of two objectives was sought. The first objective was minimization of power generation loss (which means maximizing the generated power). The second objective was minimization of certain constraints. A value of zero for the second constraint means that all constraints were satisfied. A separation of 4D was assumed between two turbines, with the rotor diameter of 77 m, and hub height of 80 m. Two wind scenarios were considered. In the first scenario, wind directions between 0° and 15°, and 90° and 105° were considered. In the second scenario, a wider spectrum of wind direction in the range of 120°–225° was assumed. Results suggested that although a

global optimal solution could not be guaranteed, yet the quality of the generated solutions was acceptable for industrial applications.

3.15. Single-objective GA of Bilbao and Alba

Bilbao and Alba [52] employed the CHC algorithm, which is a modified version of GA having some special features. CHC does not perform mutation operation to produce new solutions; instead it uses a mechanism called HUX crossover. Furthermore, a pre-defined number of individuals are chosen using the *elitist* selection approach to complete the next generation. Due to the absence of mutation and presence of elitist approach, the population tends to be homogeneous. This problem was solved through a mechanism called *incest prevention*. Moreover, the mechanism of HUX crossover was also able to preserve diversity in the population. A single objective optimization was performed with the same objective function as used by Huang [42], which required maximization of annual profit obtained from the wind farm. Katić wake decay model was used. A rotor diameter of 47 m was assumed, with the width of each cell being equal to 5D. A 10×10 grid was assumed. This resulted in a solution of binary string of size 100, where each location in the solution could take a value of '1' (representing the presence of a turbine), or a '0' (suggesting the absence of a turbine). Four test scenarios were assumed. In the first three scenarios, three different wind speeds were assumed from a single direction. The fourth scenario assumed a real wind distribution. Results suggested that the proposed CHC was a suitable algorithm to solve the problem in hand.

3.16. Single-objective GA of González et al. considering uncertainties

With further extension to their previous work [58], González et al. [53,54] proposed a GA for optimal wind farm layout design, with the investment financial risk as an important optimization factor. Their approach was based on the fact that there are a number of uncertainties that affect the profitability of a wind farm. Thus, reduction in these uncertainties would positively affect the power generation from the wind farm, and hence the profitability. They identified two key factors that introduce uncertainties. The first is the future prices of goods such as the price of the energy or the discount rate of money, which are obviously unknown. The second factor is the random nature of wind which introduces some degree of uncertainty in annual energy production, which in turn affects the profitability. In the optimization process, a single objective, namely Net Present Values (NPV) similar to that of Mora et al. [41] was considered. Furthermore, the same GA as used in [58] was assumed, having the solution coded as an integer matrix. A 2.5 km $\times$ 2.5 km square terrain, subdivided into 10×10 cells for possible wind turbine locations, was considered. Similar to their previous work [58], three kinds of restrictions such as the presence of a main road crossing the wind farm, forbidden zones, and a low load-bearing capacity zone were assumed. Experiments assumed nine wind scenarios, which mainly differed in wind directions. Results suggested that when the risk analysis is included, the optimization process of the wind farm results in solutions less sensitive to the uncertainty than the deterministic solution.

3.17. Single-objective two-level GA of González et al.

Continuing with their previous works [58,53,54], González et al. [55] made further modifications to their proposed GA. In their previous applications, they used Net Present Values (NPV) as the optimization objective. However, the proposed algorithm in [55] used two nested GAs. The main (primary) GA took into account the position, type, and hub height of the wind turbines, along with the layout of the internal network of auxiliary roads and the civil infrastructure. The output of this level was to optimize the NPV of the wind farm. For each feasible solution of this main GA, it was relatively easy to calculate most of the terms of NPV, except for those corresponding to the electricity infrastructure and associated power losses. To overcome this issue, a secondary level GA was executed for every one of the turbine layout individuals to determine its optimal electricity infrastructure. The target of this secondary GA was to minimize the sum of the investment in electricity infrastructure and the cost of the electrical losses. Other parameters and test cases remained the same as in [53,54]. Experimental analysis consisted of performance evaluation of the proposed scheme, in addition sensitivity tests, and showed the suitability of the two-level GAs to find the optimum configuration of the wind farm.

3.18. Single-objective GA of Moreno et al.

The wind farm layout design approach proposed by Moreno et al. [56] consisted of two phases. In the first phase, a greedy heuristic was used to obtain a reasonable initial solution. This initial solution was then used as a seed for the main optimization phase which was implemented using a GA. According to Moreno et al., their work had several novelties that made the problem more realistic compared to previous approaches. These novelties included a wind farm shape model, orography model, and the inclusion of benefit/cost terms in the objective function. The other uniqueness was in terms of using a seed for the proposed GA, which was not attempted before. They used Jensen's wake effect model. The cost model they adopted was a simplified version of the cost model by Mora et al. [41]. Single-objective optimization was attempted, with the aim of maximizing the following equation:

$$\phi = B_t - N \cdot C_i - \sum_{i=1}^{n} \sum_{j<1} C_{ij}^{C} \tag{12}$$

where C_i is the installation cost of wind turbines, C_{ij}^{C} is the cost of connection between turbines and road construction, both modeled as the Euclidean distance between turbine i and j. B_t is the net benefit obtained from the energy produced in t years. N stands for the number of wind turbines installed in the wind farm.

The approach of seeding the GA with the greedy heuristic proposed seeding part of the initial GA population with the greedy solution and some variations of this solution (obtained by means of mutation). Furthermore, some individuals were generated randomly and included to complete the initial population of the GA. An integer matrix representation was used for a solution. Testing of the seeded GA was done using a randomly generated shape of a wind farm with 15 different sets of wind speeds to model different orography for the wind farm. Since the shape of the wind farm was random, more emphasis was given to the cell size taken to be 10 m $\times$ 10 m, with the value of D=90 m. Comparison was done between the greedy heuristic, the GA without the seed, and the seeded GA. Results suggested that the unseeded GA demonstrated better performance than the greedy heuristic with regard to the quality of solutions. Moreover, the seeded GA outperformed both the unseeded GA as well as the greedy heuristic for all test instances.

3.19. Multi-objective GA of Khan and Rehman

Khan and Rehman [57] have proposed a multi-objective GA to design a wind farm a layout. They considered the cost per year of the wind farm and total energy produced per year by the wind

farm. They have used the objective function of the Mosetti et al. given in Eq. (1) as the basis, but modified it with regard to the aggregation scheme and calculation of objectives. Mosetti et al. used different weights for the two objectives to decide the level of preference of one objective with respect to the other. Instead of using this *weighted sum* approach, Khan and Rehman have employed fuzzy logic to aggregate the two objectives in a single objective function. To assess a solution, following fuzzy rule was used:

If a solution X has low cost per year and high output energy per year then it is a good solution.

Mathematically, this has been represented using the Unified And-OR (UAO) aggregation operator [65] as follows:

$$\mu(x) = \frac{\mu_1(x)\mu_2(x) + \nu \max\{\mu_1(x), \mu_2(x)\}}{\nu + \max\{\mu_1(x), \mu_2(x)\}} \tag{13}$$

In Eq. (13), $\mu(x)$ represents the membership value of solution x in the fuzzy set "good solution", and μ_1 and μ_2 represent the membership values of solution x in the fuzzy sets *low cost per year* and *high output energy per year*, respectively. The solution which results in the maximum value for Eq. (13) is reported as the best solution found.

The proposed GA followed the same structure as that of Mosetti et al. Binary string of size 100 was used to represent a solution. A 10×10 grid was assumed. The site selected was near the city of Dhahran, located in the eastern coastline of Saudi Arabia. Initial results were promising and further improvements in the proposed GA are underway.

3.20. Multi-objective GA of Kwong et al.

The work of Kwong et al. [29] had many similarities to previous works, with one novel aspect. Unlike other previous works, which considered cost and energy output in one form or the other as the optimization objectives, Kwong et al., for the first time, considered the level of noise generated by the wind farm as an optimization objective. A multi-objective optimization was sought, desiring maximization of energy generation and minimization of noise at the wind farm boundary. An NSGA-II version of GA [66] was employed to solve the multi-objective problem. A flat terrain, with dimensions of 2.0 km $\times$ 2.0 km, subject to a uniform, unidirectional wind speed of 12 m/s was used, while considering 15, 30, and 45 turbines. Jensen's wake decay model was assumed. As opposed to discrete version of the problem reported in many previous works, Kwong et al. allowed turbine positions to vary continuously within a cell size having side lengths of 100 m, thus relaxing proximity constraints to some extent.

4. Differential evolution and wind farm layout design problem

Differential Evolution (DE) is another nature-inspired, population-based algorithm. It was introduced by Storn and Price [18]. It employs the mutation, crossover, and selection operations similar to genetic algorithm, although the notion of these operators in the context of DE is slightly different than what is used in GA. DE is fast in convergence and uses very few control variables.

DE maintains two arrays, each of which holds a population of n-dimensional, real-valued vectors. The current population resides in the primary array while the secondary array holds vectors that are selected for the next generation. The process of selection is done through competition between the existing vectors and trial vectors. The trial vectors used by DE are formed through mutation and recombination (crossover) of the vectors in the primary array [67].

Although DE has been used for a number of optimization problems, its application to the wind farm design has been very limited. To date, only two applications have been reported in the literature, both by the same authors (refer to Table 3). These application are briefly described below.

4.1. Two-function DE of Rasuo et al.

Rasuo et al. [67,68], for the first time, attempted to use DE for wind turbine placement in a wind farm with several novelties with regard to the calculation of the fitness function. In previous approaches which used GA for wind farm design, the solution was represented as binary strings. This caused the turbines to be placed at the center of a selected cell. As opposed to this, Rasuo et al. proposed that the positions of turbines in a wind farm could be adjusted freely (instead of being in the center of each cell), resulting in further reduction of the wake effects, and therefore more wind energy could be captured. Since the optimization variables in this case are real value, a real-coded DE was engineered. To obtain more accurate wake effects, an improved wake model was used for calculation of each turbine wake shape and wake interactions. As far as the test scenarios are concerned, only one scenario was considered which assumed that the wind speed and direction were constant.

The optimization process consisted of two different optimization functions. The first function was formed as the ratio of the total energy that is obtained from the wind farm (denoted as P_{total}) versus the energy sum of the isolated wind turbine (denoted as P_{max}), for the same wind conditions at the flat terrain. This is given by

$$\text{Maximize } \frac{P_{total}}{P_{max}} \tag{14}$$

The second optimization function took into account the economical factor, i.e., investment costs. This was calculated by the simple approach, given mathematically as

$$\text{Minimize } \frac{Cost}{P_{total}} \tag{15}$$

A detailed approach about the real-coded chromosome (representing a solution) was given. Simulation results for continuous DE for both optimization functions produced promising results.

5. Particle swarm optimization and wind farm layout design problem

The Particle Swarm Optimization (PSO) algorithm was proposed by Kennedy and Eberhart [73], and is inspired by sociological behavior associated with bird flocking. The algorithm maintains a population of individuals, called particles, where each particle represents a potential solution. A particle has an adaptable velocity which is associated with position change, according to which it moves through an n-dimensional search space. Each particle is capable of remembering the best position (solution) it has reached so far. Moreover, all particles can also share their information about the search space, so there is a global best solution. A number of parameters such as the swarm size, inertia weight, w, acceleration coefficients, c_1 and c_2, and velocity clamping, V_{max}, affect the performance of the algorithm, and should be carefully tuned for highest quality results.

The idea of using Particle Swarm Optimization (PSO) for wind farm layout design did not get much attention earlier, but it is now gaining momentum. The first attempt about the use of PSO

Table 3
Characteristics of different wind farm layout design problems considered in differential evolution, particle swarm optimization, and simulated annealing algorithms. HH represents hub height, and D represents rotor diameter.

Ref.	Year	Grid	Wind scenarios	Wind turbine height and rotor diameter	Wake decay model
DE [67,68]	2010	Unspecified	Unidirectional wind with constant intensity	HH=60 m D=40 m	Developed their own model
PSO [69]	2010	Same as [39]	Three cases with different number of wind turbines	HH=60 m D=40 m	Jensen
PSO [70]	2010	Same as [40]	Same as [40]	HH=unspecified D=50 m	Jensen
PSO [71,72]	2010,2012	Wind tunnel	Case 1: wind farm with non-identical turbines Case 2: wind farm with identical turbines	HH=0.12 m D=0.12 (wind tunnel model)	Frandsen
SA [52]	2010	Same as [39]	(1) Three scenarios considering fixed direction and different wind speeds (2) Real wind distribution	HH=unspecified D=47 m	Katić
SA [48]	2009	Straight line in flat terrain	(1) Fixed hub height and uni-directional wind flow (2) Fixed hub height and bi-directional wind flow (3) Variable hub height and bi-directional wind flow	HH=Unspecified D=77 m	Jansen

for wind farm design was reported in 2010, with three more in the same year, as summarized in Table 3. These attempts are briefly described below.

5.1. Single-objective PSO of Rahmani et al.

Rahmani et al. [69] made the first attempt to solve the wind farm layout design problem using PSO. A basic version of PSO was used. They opted for a single-objective optimization as given by Eq. (2) in Section 3.2. Since the focus of their study was to compare the performance of their proposed PSO with the work of Mosetti et al. [39], Grady et al. [40], and Marmidis et al. [74], there were many similarities in terms of assumptions and test cases. A 2 km $\times$ 2 km square field was used, divided into 10 $\times$ 10 cells, with 100 possible locations to place a turbine. A cell size equal to 5D was used. Three different test instances were assumed which differed only in the number of wind turbines used. Simulation results revealed suitability of the proposed PSO to solve the problem.

5.2. Single-objective PSO of Wan et al.

Wan et al. [70] proposed a PSO based approach for layout design of a wind farm. A PSO having the factors of inertia weight, maximum velocity, and constriction factor were used. As opposed to some previous attempts with other algorithms, which used discrete positions for the wind turbines (i.e., in the center of the cell), Wan et al. assumed a continuous space. That is, turbines could be placed anywhere within the perimeter of the wind farm. However, the restriction was to maintain a minimum distance of 4D between turbines, with the value of D=50 m. A square shaped wind farm partitioned into 10 $\times$ 10 grid was assumed. A single-objective optimization was sought, with the objective being the maximization of generated power, as used by Grady et al. [40] given in Eq. (2). Moreover, same test cases as used by Grady et al. were considered to evaluate the performance of the proposed PSO.

5.3. Single-objective PSO of Chowdhury et al.

Chowdhury et al. [71,72] proposed a PSO to design a wind farm with the aim of exploring the influences of the number of turbines, the farm size, and the use of a combination of turbines with differing rotor diameters, on the optimal power generated by a wind farm. They employed their recently developed Unrestricted Wind Farm Layout Optimization (UWFLO) which allows for the use of a combination of turbines with differing rotor diameters in a wind farm. Their proposed PSO was a *mixed-discrete* version of the basic PSO, where the design space is divided into a discrete domain and continuous domain. Another feature of the proposed PSO was that it used the principle of constrained non-dominance [75] to compare the particles (candidate solutions). Single-objective optimization was performed with the aim of maximizing the total power generation, measured as the *wind farm efficiency*, and represented mathematically as:

$$\eta_{farm} = \frac{P_{farm}}{NP_{rated}} \tag{16}$$

where P_{farm} is the total power generated by the wind farm, N is the number of identical turbines, and P_{rate} is the rated power of the wind turbines used.

Chowdhury et al. used Frandsen wake decay model. Two test scenarios were used using wind tunnel models, to evaluate the performance of the algorithm. In the first test cases, wind farm with non-identical turbines (having different rotor diameters) was considered. In the second case, wind farm with identical turbines that can adapt to wind conditions similar to commercial turbines were assumed. Results showed that the use of an optimal combination of turbines with differing rotor diameters significantly improve the net power generation.

5.4. Single-objective PSO of Bilbao and Alba

Bilbao and Alba [76] employed Geometric PSO (GPSO) with the objective of maximizing the annual profit obtained from the farm, as represented by Eq. (5). The key feature of GPSO is with regard to using a multi-parental recombination of particles. This leads to the generalization of a mask-based crossover operation, proving that it respects four requirements for being a convex combination in a certain space. In this way, the mask-based crossover operation substitutes the classical movement in PSO, based on the velocity and position update operations, only suited for continuous spaces. A solution was represented as a binary string. With regard to other technical aspects (e.g., wake effect model, hub height, rotor diameter, etc.), Bilbao and Alba used the same parameters and test cases as used in their previous work [52] described in Section 3.15.

6. Simulated annealing and wind farm layout design problem

Simulated Annealing (SA) [14,15] is a well-known optimization algorithm that has been successfully applied to a number of complex optimization problems. As opposed to GA, DE, and PSO, which maintain a population of solutions in each iteration, SA maintains a single solution which is perturbed throughout the execution of the algorithm. The algorithm has two main steps: initialization and the Metropolis procedure. The initialization step involves generating a feasible solution. This solution is then passed to the Metropolis procedure which perturbs the solution. If the fitness (quality) of the new (perturbed) solution is higher than the fitness of the current solution, then the new solution is readily accepted. Otherwise, the new solution is accepted probabilistically based on the *metropolis criterion* given by $P(random < e^{-\Delta h/T})$, where *random* is a random number in the range 0–1, Δh represents the difference in the fitness of current solution and new solution, and T represents the *annealing temperature*. SA has a number of control parameters which have an impact on the performance of the algorithm. These parameters include the initial temperature, T_0, the cooling rate, α_{SA}, the constant, β_{SA}, and the length of Markov chain, M, which represents the time until the next parameter update. Inappropriate values for these parameters may result in non-optimal solutions.

Unfortunately, despite being a well-known optimization algorithm, SA has received less attention than population-based algorithms. So far, only two research works utilizing SA for wind farm layout design have been reported in the literature (refer to Table 3), as described below.

6.1. Single-objective SA of Bilbao and Alba

Apart from implementing a CHC algorithm, as described in Section 3.15, Bilbao and Alba [52] also implemented a SA algorithm using the same objective function, test cases, and other wind farm related parameters. Moreover, binary string was used to represent a solution.

6.2. Single-objective SA of Acero et al.

In addition to implementing a GA (refer to Section 3.10), Acero et al. [48] also implemented a SA. One special feature of their SA was that it allowed for the variation of the temperature inside a Markov chain every time a transition was accepted. Other aspects of their implementation such as the objective function, solution representation, test cases, and other characteristics of the wind farm were the same as described in Section 3.10.

7. Comparative studies of algorithms

Most of the attempts that have been made to design a wind farm with iterative algorithms have focussed on using a single algorithm to design the layout of a wind farm. There are very few studies that implemented multiple algorithms for the same problem and then compared the mutual performance.

Bilbao and Alba [52] also compared their proposed GA (CHC) and SA. As listed in Table 1, there were four test scenarios. In the first three scenarios, fixed wind direction and different wind speeds were assumed, while in the fourth scenario, real wind conditions were assumed. In all four scenarios, GA obtained better average fitness value, better power output, and better efficiency than SA, proving that GA was more suitable than SA for this particular set of test cases.

Bilbao and Alba [76] also compared their above GA with GPSO for the first three scenarios as mentioned in the previous paragraph. For the first scenario, GA obtained better average fitness value, better power output, and better efficiency. However, GA utilized more execution time and more evaluations to find the best solution than GPSO. For the second scenario, both GA and GPSO obtained the same average fitness value, power output, and efficiency. However, GA took less execution time as it needed less evaluations than GPSO. Finally, for the third scenario, GA again obtained better results in most of the metrics than GPSO, although the final configuration for the wind farm was the same for both algorithms.

Table 4
Characteristics of the differential evolution, particle swarm optimization, and simulated annealing algorithms considered in the review.

Ref.	Type	Optimization objectives	Solution representation
[67,68]	Centralized	Single-objective	Real valued string
[69]	Centralized	Single-objective	Binary string
[70]	Centralized	Single-objective	Unspecified
[71,72]	Centralized	Single-objective	Unspecified
[52]	Centralized	Single-objective	Binary string
[48]	Centralized	Single-objective	Binary digits

The comparison of GA and SA in the work of Acero et al. [48] revealed different outcomes. For all test cases, as listed in Table 4, it was found that simulated annealing produced better results and took less time to achieve them. On the other hand, genetic algorithms found acceptable results but took more time and more evaluations of the objective function. In particular, for case 3, both algorithms found the optimal solution where simulated annealing needed 9000 evaluations of the objective function while genetic algorithms had to evaluate about 13,000 times.

Wan et al. [70] compared PSO with the GA of Grady et al. [40]. As mentioned in Section 5.2, Wan et al. used the same objective function and test cases as used by Grady et al. Comparison of the two algorithms was reported only with respect to the objective function, which was taken as the power produced by the wind farm. For the three test cases used, the PSO of Wan et al. achieved improvements of 6.34%, 4.13%, and 4.02% for cases 1,2, and 3, respectively.

8. Research opportunities and challenges

This paper provides a brief survey of research on the use of iterative non-deterministic algorithms for wind farm layout design. Based on this survey, several challenges and future research opportunities are identified as follows.

- *Benchmark for wind farm layout design problem*: From the perspective of computational science, performance of a newly proposed algorithm is evaluated through benchmark tests. Benchmarking consists of running the proposed algorithm on a certain data set which is globally accepted as the standard test suite by the researchers working in that domain. The results are then compared with another algorithm which has already been applied on the same problem using the same standard data set. With regard to wind farm layout problem, no benchmark test cases exist, which makes it almost impossible to asses as how well the proposed algorithm has worked. This has been the very obvious drawback of all studies covered in this survey, since each study assumed its own conditions (such as wind speed, wind direction, terrain type, wake model, etc.). In order to evaluate the true performance of an iterative non-deterministic algorithm, researchers must develop a set of standard test scenarios to be adopted as benchmarks.
- *More realistic objective functions*: With regard to the issue of designing the objective function to be optimized, majority of the studies surveyed in this paper focused only on one

objective while ignoring other important objectives. For example, emphasis was either put on the power generation with less or no consideration on the operational and other costs as well as noise levels, or vice versa. Furthermore, several objective functions included factors (such as the cost of the wind generator, the tower and the installation, etc.) which do not play any role in the optimization process (since these costs would remain the same regardless of the layout configuration, assuming that the number of turbines in any configuration remains the same), hence decreasing the computational efficiency of the algorithm used. Therefore, it is essential to identify those objectives which contribute significantly to the overall optimization process and enhance the computational efficiency of the algorithm. Furthermore, efficient and realistic objective functions need to be designed that reflect the actual requirements of the wind farm under consideration.

- *More efficient multi-objective optimization approaches*: Most of the studies in this survey considered optimization of a single objective (e.g., either emphasizing the cost or the power generation) which does not reflect the true nature of the problem, since improving only one objective will degrade the quality of other objectives due to their conflicting nature. Therefore, it would be more logical and realistic to consider multiple objectives in the design. However, adopting an efficient multi-objective approach is a key factor in the success of an iterative non-deterministic algorithm. For example, the multi-objective approaches adopted by Mosetti et al. [39], and Emami and Noghreh [49] were based on the 'Weighted Sum Method' (WSM) which has several weaknesses. For example, a small change in weights may result in big changes in the objective vectors [77]. Moreover, significantly different weights may produce nearly similar objective vectors [78]. WSM also suffers from not satisfying Pareto optimality, which is considered one of the fundamental aspects of multi-objective optimization problems. Considering the sensitivity of the wind farm layout design problem, and the capital involved therein, it becomes extremely important to choose the most efficient multi-objective optimization approach to guarantee high quality, efficient layout designs.
- *More focus on algorithm development and efficiency*: The studies presented in this survey focused on different dimensions of the wind farm layout design problem, but did not give due attention to the algorithmic aspects of the adopted techniques. One such aspect was the selection of appropriate algorithm parameters and sensitivity analysis. As discussed in previous sections, all algorithms surveyed in this paper have certain parameters which have a significant impact on the quality of a solution. Therefore, it is very important to find the most appropriate values of these algorithm parameters to ensure optimal or near-optimal solutions. This is only possible after trial and error of different values for each parameter. Not only this, it is also important to investigate which algorithm parameter has the highest impact on the quality of the final solution, which is only possible through parameter sensitivity analysis. Furthermore, majority of the papers applied the basic, older versions of the iterative non-deterministic algorithms, rather than the advanced, more efficient versions that are built upon the advance features such as hybridization, parallelization, and dynamic assignment of parameters. Hybridization refers to the phenomenon of incorporating/embedding characteristics of one iterative non-deterministic algorithm into another. Parallelization is a computational technique in which different sub-tasks of an algorithm are run on multiple computers in parallel, rather than running all tasks on a single computer. This approach generates the final output in less computational time. Dynamic assignments of parameters are another advance approach in which the algorithm is modified in such a way that it adjusts its parameters by itself after extracting certain information from the input data. This saves user the time spent in manually adjusting the algorithm parameters after trial and error which is cumbersome and time consuming process. The literature in the domain of iterative algorithms is filled with examples where advanced algorithms having hybrid/parallel/dynamic features produced higher quality solutions than their basic counterparts. Therefore, it is important to give attention to all above aspects to develop more efficient and robust algorithms to solve the problem in hand.
- *Comparative studies of algorithms*: Another aspect that deserves attention is the comparative studies of the algorithms. It is obvious from the above review that the focus has remained on applying one algorithm to solve the wind farm layout problem, without comparing the proposed technique to other approaches or algorithms. Comparative studies provide an in-depth view of the algorithms' performance. For example, algorithm 'A' may produce higher quality results than algorithm 'B', but at the expense of more computational time or hardware requirements, etc. Without comparative studies, true behavior of an algorithm from all dimensions and aspects cannot be evaluated.
- *Non-deterministic nature of the algorithms*: A very fundamental issue that has not been addressed in the studies is the non-deterministic and random nature of the iterative algorithms. It is a well-known fact that different runs of iterative non-deterministic algorithms produce different solutions, and therefore a general strategy is to have several runs and then take the one that results in the best configuration. This has not been done in any of the studies. This also gives rise to the necessity of incorporating problem specific domain knowledge into the algorithms under study to reduce randomness and computational time.
- *Utilization of other iterative non-deterministic algorithms*: One other aspect that has been highlighted by this review is that the research on using iterative non-deterministic algorithms for the wind farm layout design problem has been limited to four algorithms, namely genetic algorithms, particle swarm optimization, differential evolution, and simulated annealing. Even in these four algorithms, the share of genetic algorithms is more than 75%. This points out to the fact that the researchers need to pay attention to a number of other iterative non-deterministic algorithms that have performed well on problems similar to the one considered in this review. Some of these, such as Tabu Search, Simulated Evolution, Stochastic Evolution, Ant Colony Optimization, and Honeybee Colony Optimization, have already been mentioned in Section 1. Other promising candidates are Memetic Algorithms [79], Artificial Immune Systems [80], Biogeography Based Optimization [81], Extremal Optimization [82], Firefly Algorithm [83], and Cuckoo Search Algorithm [84].

9. Concluding remarks

Wind farm layout design is a complex optimization problem that requires optimization of one or more design objectives such as financial cost, generated power, and noise level. On the basis of studies presented in this paper, iterative non-deterministic algorithms such as genetic algorithms, differential evolution, particle swarm optimization, and simulated annealing are some of the most suitable approaches to address the problem for generating efficient, rather optimal, layouts of wind farms. However, as listed

above, there are still many open issues that need to be addressed in order to come up with approaches that are more efficient and computationally less expensive. These issues include developing benchmark cases for performance evaluation, constructing more efficient and realistic objective functions, using more efficient multi-objective optimization approaches, giving more attention to algorithm development and efficiency, putting more focus on comparative studies of the algorithms as well as understanding the non-deterministic nature of algorithms. It was observed that genetic algorithm has been used in more than 75% studies surveyed in this paper. Therefore, emphasis should also be put on utilizing other iterative non-deterministic algorithms for a more diversified and rich comparative research in the domain of wind farm layout design. From the current rate of growth of iterative non-deterministic algorithms in wind farm layout design problems, it is envisioned that these algorithms will continue to grow as important optimization approaches to solve the problem in a more efficient way.

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